An Artificial Neural Network Method for Optimal Generation Dispatch with Multiple Fuel Options

Prof (Dr) P K Hota, *Fellow*

A K Barisal, *Member*

Dr S K Dash, *Non-member*

This paper presents an artificial neural network method to solve the optimal generation dispatch problem with multiple fuel options. Traditionally, in the optimal generation dispatch problem, the cost function for each generator is approximately represented by a single quadratic function. However, it is more realistic to represent the generation cost function for fossil fired plants as a segmented piece-wise quadratic functions, as in the case of valve point loading. Some generation units especially, those units which are supplied with multiple fuel sources (gas and oil) are faced with the problem of determining which is the most economical fuel to burn. The proposed method has applications to fossil fired generating units capable of burning gas and oil, etc, as well as, other problems which result in multiple intersecting cost curves for a particular unit. An advantage of this method is the capability to optimize over a greater variety of operating conditions. The simulation results show that the solution method is practical and valid for real time operation.

Keywords : Optimal generation dispatch; Multiple fuel options; Hybrid cost function; Radial basis function network; Hopfield neural network

INTRODUCTION

Traditionally in economic load dispatch (ELD) problem, the cost function for each generating unit has been approximately represented by single quadratic function. It is more realistic, however, if the cost curve of each generating fossil-fired unit can be represented as a segmented piece-wise quadratic function[2], as in the case of valve point loading. For piece-wise quadratic cost function, the generating units are supplied with multiple fuel sources, such as,

(i) gases or gases with different heat content,

(ii) coal or different heat content of coal, and

(iii) oil or different heat content of oil.

Thus, the cost function of any fossil fired unit can be partitioned into different segments for multiple fuels. Each segment of multi-fuel cost function is being associated with different types of fuel. For this reason any or single unit for multi-fuel option can be burnt with at least two types of fuels. Some generation units especially, those units, which are supplied with multiple fuel sources (gas/ oil/ coal, etc) are faced with the problem of determining which is the most economical fuel to burn. As fossil fuel costs increase, it becomes even more important to have a good model for the production cost of each generator. In this work, the piece wise quadratic function is used to represent multi-fuel which is available to each generating unit. For any given unit with multiple cost curves, these curves can be superimposed as shown in Figure 1. The resulting cost function is known as 'hybrid cost' function[3]. The hybrid cost function is known as piece-wise cost function also. The hybrid incremental cost function can be obtained from hybrid cost function. The economic load dispatch for multiple-fuel generation schedule of any unit is done in such a way that the fuel cost is at minimum level, *ie*, burning of fuel of each unit is done economically. Therefore, an efficient method to obtain the generation schedule of each unit for such type of ELD problem is needed to be developed. There has been a growing interest in neural network models with massively parallel structures, which mimic the human brain[4]. Owing to the powerful capabilities of neural networks, such as, learning, optimization and fault tolerance, neural networks have been applied to the various fields of complex, non-linear and large-scale power systems[5-7]. Novak has described the various fields of power system where the radial basis neural network can be applied successfully[8]. Park and Sandberg have described the radial basis function networks as universal tool for function approximation[9]. The most promising advantage of this network over back-propagation neural network is its auto-configuring architecture. Besides, the training time for a practical sized problem in case of radial basis function network is significantly less as compared to that of the back-propagation network. On the other hand, the Hopfield neural network[10-11] has been applied to various fields since Hopfield proposed the model in 1982. In the problem of optimization, the Hopfield neural network has a well demonstrated capability of finding solutions to difficult optimization problems. The TSM (traveling salesman problem)[12], typical problems of NP (non-deterministic polynomial) complete class, A/D conversion, linear

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Prof (Dr) P K Hota and A K Barisal are with the University College of Engineering, Burla, Sambalpur 768 018; while Dr S K Dash is with the Department of Electrical Engineering, Gandhi Institute for Technological Advancement, Bhubaneswar 751 012.

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programming and job-shopping schedule are good examples, which the Hopfield network provides with solutions[13-14]. In the field of power systems, the Hopfield network has been applied to unit commitment[15], and economic load dispatch problems[16-18]. This paper particularly presents a new method to solve the problem of optimal generation dispatch with multiple fuel options using a radial basis function neural network along with a heuristic rule based search algorithm and a Hopfield neural network. The simulation results show that the solution method is practical and valid for real-time operation. An advantage of the proposed method is its capability to optimize over a greater variety of operating conditions. The proposed ANN method has applications to fossil fuelled generation units capable of burning coal, gas, and/or oil, as well as other problems which result in multiple intersecting cost curves for a particular generating unit.

PROBLEM FORMULATION

Generation Dispatch Problem with Multi-fuel Options

The modern power system experiences show that the cost functions of fossil-fuel fired generating units are piece-wise quadratic functions. The piece-wise quadratic cost functions are generally equipped with either the provision of multi-fuels or oil/gases with different heat contents. In general, these lead to hybrid cost functions and hybrid incremental cost (IC) functions as given here[18]. The formulation of hybrid cost functions and hybrid incremental cost functions are detailed by Hota and Dash[20].

Economic Load Dispatch Problem

The ELD problem is to find the optimal combination of power generation which minimizes the total fuel cost while satisfying the total required demand. In this paper, the cost function is

$$C = \sum_i (a_i + b_i P_i + c_i P_i^2) \tag{1}$$

where C is the total cost; a_i, b_i, c_i, cost coefficients of generator i; P_i, the generated power of generated i.

In minimizing total fuel cost, the following constraints should be satisfied.

Power Balance

$$P_D + L = \sum_i P_i \tag{2}$$

where P_D is the total load an d L, the transmission loss.

The transmission loss can be represented as

$$L = \left[\sum_{i=1}^{m} \left(D_i P_i^2\right)\right] \tag{3}$$

where m is the number of generators; and D_i, the transmission loss coefficients.

Maximum and Minimum Limits of Power

The generator power of each generator should be laid between P_i^{max} maximum and P_i^{min} minimum real power output of i^{th} unit, respectively. That is,

$$P_i^{min} \le P_i \le P_i^{max} \tag{4}$$

ANN BASED METHOD

The basic block diagram of the proposed ANN method to solve the optimal generation dispatch problem with multiple fuel options has been shown in Figure 1. Initially, a numerical technique[20] is applied to find out the economic fuel option for each unit corresponding to a particular load demand. The dotted box shows this for generation of training patterns for the radial basis function ANN. Once this ANN is trained, then for a given load demand, a preliminary economic fuel option for each generating unit is obtained. In fact the fuel options are integer values like 1, 2 or 3, etc. But, in the preliminary economic fuel option results, one may get fractional values like 1.008, 0.987, etc. Therefore, a simple heuristic rule based algorithm is developed to reach a correct economic fuel option, *ie*, an integer value for each output. After obtaining the economic fuel option for each generating unit corresponding to a given load demand, the optimal generation dispatch problem becomes a simple ELD problem whose result is obtained by a Hopfield neural network which satisfies the operational constraints. As shown in Figure 2, the design procedure of the proposed ANN technique consisting of radial basis function ANN, Hopfield ANN methods along with a heuristic rule based search algorithm for optimal generation dispatch solutions with multiple fuel options involves five major steps, *viz*, training set creation, training, testing of radial basis function ANN, heuristic search and Hopfield ANN. In the proposed ANN technique, the economic fuel options are obtained by the numerical technique[20]. For determination of economic fuel option for each generating unit, neural network of supervised learning is needed. This is because, the economic fuel option for each generating unit (outputs) for each total system load demand (input) in the training set are required to be known

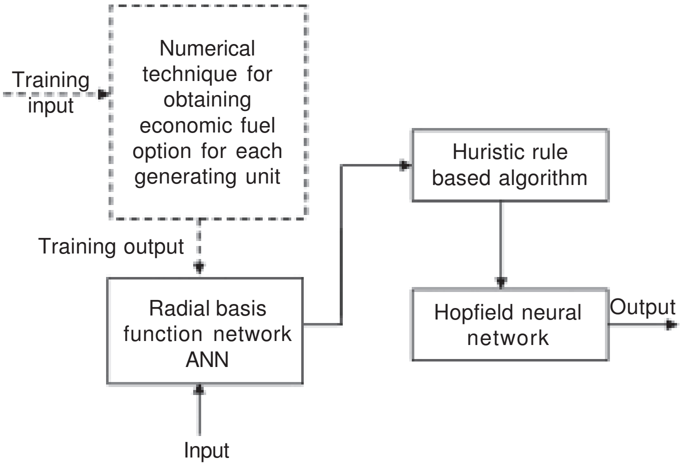

Figure 1 Block diagram of proposed ANN technique for optimal generation dispatch with multiple fuel options

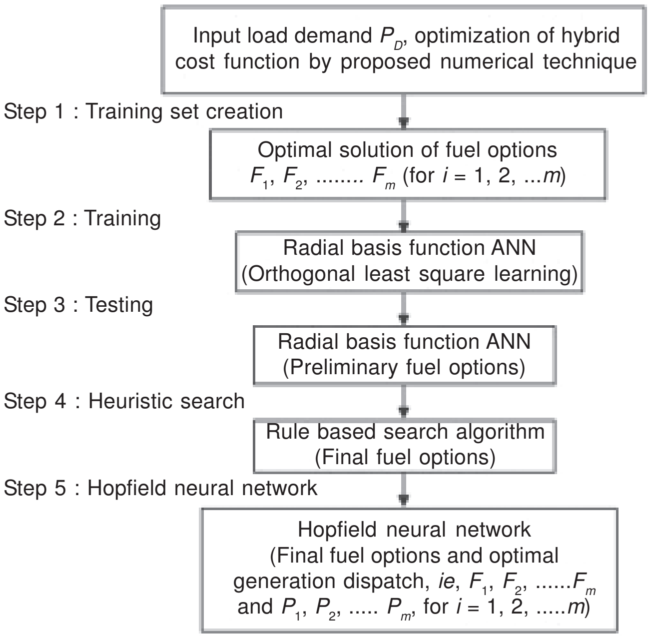

Figure 2 Design procedure of the proposed ANN technique for optimal generation dispatch problem with multiple fuel options

in advance by some suitable method. A radial basis function ANN called as RBANN is employed in the present work for training and testing due to its auto configuring architecture and faster learning ability. In the training process, the RBANN is presented with a series of pattern pairs, each pair consists of an input pattern and a target output pattern. The training pattern '*p*' is described by

$$t(p) = \{(\text{input }(p)), (\text{output }(p))\}$$

$$= \{(P_D(p)), (F_1(p), F_2(p), \ldots, F_m(p))\} \tag{5}$$

Here, $F_j(p)$ indicates the fuel option of j th generating unit corresponding to p^{th} training pattern. The sum of the squared errors (SSE) between the actual and the desired (target) outputs over the entire training sets is used as the measure to find out the convergence of the network. The RBANN used is trained by the orthogonal least squares learning algorithm. Training is continued until the given error goal in terms of SSE is reached. Once the RBANN is trained, thereafter only the steps 3 and 4 are used to obtain the economical fuel option for each generating unit for any given load PD. In the step 3 only a preliminary (non-integer) economical fuel options may be obtained. Therefore, a heuristic rule based search algorithm is developed in the step 4 to reach a correct (integer) economical fuel option for each unit. Once the economical fuel options are found out, then the optimal generation dispatch is merely an ELD problem which is solved by a Hopfield neural network in final step (step 5).

Heuristic Rule based Search Algorithm for Determination of Final Economical Fuel Options

In this work, the given heuristic rules are applied to transform the preliminary fuel option results (non-integer values) into integer values.

Rule 1: $F_j = k$ if, $k \le F_j < k + 0.5$ for j =1, 2,…,m and k = 1, 2,…,n (6)

Rule 2: $F_j = k + 1$ if, $k + 0.5 \le F_j \le k + 1$ for j =1, 2,…,m and k = 1, 2,…,n (7)

where m is the number of generating units; n, the number of fuel options; and F_j is the fuel type of j th generating unit.

Hopfield Neural Network

Hopfield neural network model is a single layer recursive neural network, where the output of each neuron is connected to the input of every other neuron. There is an external input to the each neuron. In a Hopfield network, all connective weight values are calculated initially from system data. Then as patterns or input values are applied, the network goes through a series of iterations until it stabilizes on a final output. Thus, the values of neuron inputs and the outputs change with time and form a dynamic system. It is important to ensure that the system will converge to a stable solution. This requires finding a bounded function (a Lyapunov or energy function) of the state variables such that all state changes result in a decrease in energy. There are two types of Hopfield neuron model. The original model of Hopfield neural network used a binary neuron model. The continuous and deterministic model of the Hopfield neural network[19] is based on continuous variables and responses but retains all of the significant behaviours of the original model and hence, used in the present work. The output variable V_i for neuron i has the range $V_i^0 \le V_i \le V_i^1$ and the input-output function is a continuous and monotonically increasing function of the input U_i to neuron i. The typical input-output function $g_i(U_i)$ is a sigmoidal function.

The dynamics of the neuron is defined by

$$dU_i/dt = \sum_j T_{ij}V_j + I_i \tag{8}$$

where $V_i = g_i(U_i)$; the output value of the neuron i.

$$g_i(U_i) = 1/(1+\exp(-U_i/u_0) \tag{9}$$

where g_i is the input-output function of the neuron i ; and u_0 is a coefficient that determines the shape of the sigmoidal function.

The energy function of the continuous Hopfield network is similarly defined as

$$E = -1/2\sum_i\sum_j T_{ij}V_iV_j - \sum_i I_iV_i \tag{10}$$

and its time derivative is given by

$$dE/dt = -1/2\sum_i\sum_j T_{ij}[V_j(dV_i/dt) + V_i(dV_j/dt)] - \sum_i I_i(dV_i/dt) \tag{11}$$

After simplification

$$\mathrm{d}E/\mathrm{d}t = -\sum_i g_i\left(U_i\right)\left(\mathrm{d}U_i/\mathrm{d}t\right)^2$$

From this, it can be seen that dE/dt is always less than zero because g_i is a monotonic increasing function. Therefore, the network solution moves in the same direction as the decrease in energy. The solution seeks out a minimum of E and comes to a stop at such point.

Mapping of the ELD into the Hopfield Neural Network

In order to solve the ELD problem, the following energy function is defined by combining the objective function with the constraint as defined by equation (1) and equation (2), respectively.

$$E = A(P_D + L - \sum_i P_i)^2/2 + B\sum_i(a_i + b_iP_i + c_iP_i^2)/2 \tag{12}$$

where $A \geq 0$ and $B \geq 0$ are weighting factors.

The synaptic strength and the external input are obtained by mapping the above energy function into the Hopfield energy function as described by equation (12) into the Hopfield energy function in equation (10). First by assuming that the loss L is constant, the equation (12) is expanded and compared to equation (10) in which V_i and V_j correspond to P_i and P_j, respectively.

$$E = A[(P_D + L)^2 - 2(P_D + L)(\sum_i P_i) + (\sum_i P_i)^2]/2 + B\sum_i(a_i + b_iP_i + c_iP_i^2)/2$$

$$= A(P_D + L)^2/2 - \sum_i[A(P_D + L) + Bb_i/2]P_i + \sum_i\sum_i(A + Bc_i)P_iP_i/2 + \sum_{i\neq j}\sum A P_iP_j/2 + B\sum_i a_i/2 \tag{13}$$

Thus, by comparing equation (10) with equation (13), the synaptic strength and external input of neuron *i* in the Hopfield network are given by

$$T_{ii} = -A-Bc_i \text{ and } T_{ij} = -A \tag{14}$$

$$I_i = A(P_D + L) - Bb_i/2$$

The differential synchronous transition model[18] used in the computation for this Hopfield neural network is

$$U_i(k) - U_i(k-1) = \sum_j T_{ij}V_j(k) + I_i \tag{15}$$

$$V_i(k+1) = g_i[U_i(k)] \tag{16}$$

Accordingly, the output value P_i can be obtained by this Hopfield neural network and the transmission loss can be calculated by the loss formula as described in equation (3). Again the calculated loss is assumed as a constant value and thereafter the above process is repeated. In representing a large value with the neural network, the binary number representation requires a large number of neurons which is a clear disadvantage. Therefore, in this work a modified sigmoidal function as suggested by Park, *et al*[18] is used, namely,

$$V_i = g_i(U_i) = (P_i^{\max} - P_i^{\min})(1/(1 + \exp(-U_i/u_0))) + P_i^{\min} \tag{17}$$

SYSTEM STUDIES

The test system consisting of four generating units with unit 1 supplied with two types of fuels and other remaining units supplied with three types of fuels, has been considered for the performance evaluation of the proposed algorithm. The hybrid cost coefficients, *ie*, the cost curve coefficients of each unit corresponding to different types of fuel are adopted from Hota and Dash[20]. The minimum and maximum generation capacity of each unit corresponding to each type of fuel options are also adopted from the same reference. For determination of economic fuel option of each thermal unit, neural networks of supervised learning are needed. This is because, the optimal fuel option of the thermal units (outputs) for each total system load demand (input) in the training set are required to be known in advance by some suitable method. A radial basis function ANN called as RBANN is employed in the present work for training and testing due to its auto configuring architecture and faster learning ability. The numerical technique[20] has been applied to create the necessary training set. A radial basis function ANN model, namely, RBANN is designed for the purpose. There is only one input node (load demand) for the model. The optimal fuel options of the thermal units in the system, *ie*, F_1, F_2...,F_m are the output nodes. Therefore, there are four output nodes for the RBANN. The number of neurons in the single hidden layer is equal to the number of iterations required for training and is set adaptively for RBANN. It is not unusual to get good performance on training data followed by much worse performance on test data. This can be guarded against by ensuring that the training data are uniformly distributed. Two different cases were computed by the proposed ANN technique, *ie*, (i) optimal generation dispatch with multiple fuel options without considering losses and (ii) optimal generation dispatch with multiple fuel options considering losses. For both the test cases, to train the networks PD was varied in the range 850 MW to 950 MW in steps of 5 MW. Therefore, 21 different training patterns were generated covering the system load from 850 MW to 950 MW for each test case. Two different radial basis function networks namely, the RBANN1 for test case 1 and RBANN2 for test case 2 were trained with their corresponding 21 patterns to reach the error-goal (convergence target) which was SSE = 0.001. Two different neural networks are used as the outputs, *ie*, the optimal fuel options for same load demand P_D for loss inclusion case and without loss case may be different. However, their architecture remains same. RBANN1 and RBANN2 required 19 and 20 iterations (epoch), respectively, in reaching the convergence target. To achieve the best performance on the test data and good generalization an appropriate value of spread factor (*SF*) is set. Computations were carried out for different values of *SF* to find the best value of *SF*. For a given set of test patterns the percentage mean absolute error (% MAE) is recorded for each value of *SF*. Then the value of *SF* corresponding to the minimum of the % MAE is taken as the best value of *SF*. Accordingly, the best *SF* is found to be five for both RBANN1 and RBANN2. For the performance evaluation of the RBANN, four different load levels other than those in training sets but within 850 MW to 950 MW are considered. These test cases were generated by proposed numerical technique. The test cases were computed by the RBANN1, which was trained earlier taking the best value of *SF*, *ie*, five. The final optimal fuel options obtained from the RBANN1 along with heuristic rule based search algorithm was compared with those obtained from numerical method[20] and the comparison is shown in Table 1. From this table, it is observed that the optimal fuel options obtained from RBANN1 along with heuristic rule based search algorithm matches to that of the numerical method. Similarly, Table 2 shows the comparison of final optimal fuel options obtained from the RBANN2 along with heuristic rule based search algorithm and those obtained from the numerical method. The RBANN2 results matches to that of the numerical method.

Simulation of Hopfield Neural Network

After obtaining the economic fuel option for each generating unit corresponding to a given load demand, the optimal generation dispatch result is obtained by a Hopfield neural network which satisfies the operational constraints. During simulation, it was found that the assumed initial solutions did not affect the results for different cases.

Table 1 Comparison of optimal fuel options obtained from RBANN1 along with heuristic rule based search algorithm and the numerical method

Load, MW	Generator number	Fuel options from		
		RBANN1	Heuristic rule	Numerical method[20]
902	1	2.1314	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
912	1	2.0281	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
922	1	1.9957	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
932	1	2.0041	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3

Table 2 Comparison of optimal fuel options obtained from RBANN2 alongwith heuristic rule based search algorithm and the numerical method

Load, MW	Generator number	Fuel options from		
		RBANN2	Heuristic rule	Numerical method[20]
902	1	2.0066	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
912	1	2.0014	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
922	1	1.9992	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3
932	1	1.9953	2	2
	2	1.0000	1	1
	3	1.0000	1	1
	4	3.0000	3	3

Determination of Weighting Factors

Determination of weighting factors in case of Hopfield neural network is very crucial in achieving the optimal generation schedules. *A* is the penalty factor to the constraint of the total load demand and *B* is the penalty factor to the constraint of the objective function. It was observed that when *A* was

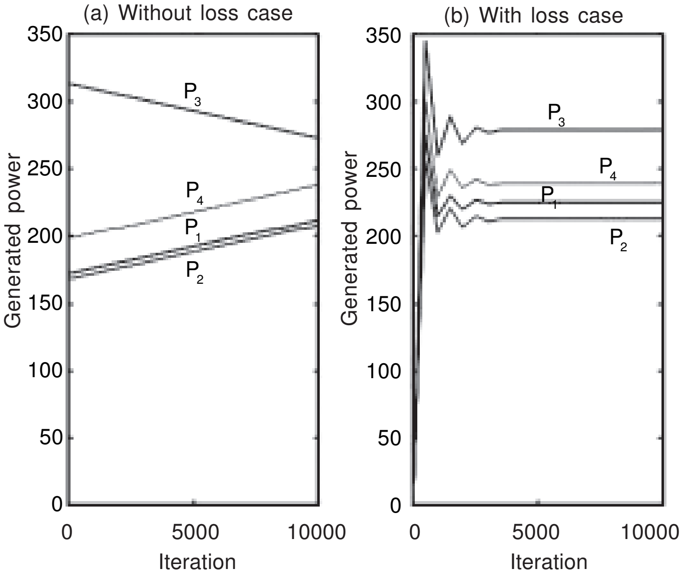

Figure 3 Convergence characteristics of Hopfield neural network

Table 3 Comparison of optimal generation dispatch results obtained from Hopfield neural network and the numerical method without considering loss

Load, MW	**Numerical method**[20]		**Hopfield neural network method**		**Power mismatch,** MW
902	Gen 1, MW	202.3490	Gen 1, MW	202.3325	0.0501
	Gen 2, MW	204.5093	Gen 2, MW	204.5021	
	Gen 3, MW	260.4127	Gen 3, MW	260.3917	
	Gen 4, MW	234.7291	Gen 4, MW	234.7237	
	Total power, MW (P_1+P_2+P_3+P_4)	902.0001	Total power, MW (P_1+P_2+P_3+P_4)	901.9500	
	Total cost, Rs/h	172.0293	Total cost, Rs/h	172.0070	
912	Gen 1, MW	205.6459	Gen 1, MW	205.5451	0.3001
	Gen 2, MW	205.9714	Gen 2, MW	205.9273	
	Gen 3, MW	264.6222	Gen 3, MW	264.4962	
	Gen 4, MW	235.7606	Gen 4, MW	235.7314	
	Total power, MW (P_1+P_2+P_3+P_4)	912.0001	Total power, MW (P_1+P_2+P_3+P_4)	911.7000	
	Total cost, Rs/h	176.5631	Total cost, Rs/h	176.4253	
922	Gen 1, MW	208.9405	Gen 1, MW	208.8745	0.1999
	Gen 2, MW	207.4331	Gen 2, MW	207.4032	
	Gen 3, MW	268.8315	Gen 3, MW	268.7474	
	Gen 4, MW	236.7948	Gen 4, MW	236.7749	
	Total power, MW (P_1+P_2+P_3+P_4)	921.9999	Total power, MW (P_1+P_2+P_3+P_4)	921.8000	
	Total cost, Rs/h	181.2195	Total cost, Rs/h	181.1252	
932	Gen 1, MW	212.2360	Gen 1, MW	211.9715	0.8001
	Gen 2, MW	208.8946	Gen 2, MW	208.7774	
	Gen 3, MW	273.0401	Gen 3, MW	272.7052	
	Gen 4, MW	237.8294	Gen 4, MW	237.7459	
	Total power, MW (P_1+P_2+P_3+P_4)	932.0001	Total power, MW (P_1+P_2+P_3+P_4)	931.2000	
	Total cost, Rs/h	185.9986	Total cost, Rs/h	185.6118	

bigger than 0.5 regardless of B values, the network oscillated. Usually, when there is self-feedback ($T_{ii} \neq 0$), the solutions can be in oscillation as reported by Park, *et al*[18]. Through simple trial and error method, it was found that $A = 0.5$ and $B = 0.06$ were appropriate values. The inequality constraints of maximum-minimum limits are dealt by the sigmoidal function variation as shown in equation (17). The results of different case studies are shown in Table 3 and Table 4, respectively, for without loss and loss inclusion cases and compared with those of numerical technique[20]. The results of the Hopfield network method shows small error in power balance (the mismatch power is 0.8001 MW in without loss case and 0.9141 MW in loss inclusion case). When this error is converted into the fuel cost of a power plant with the highest cost function, the total cost increase is extremely small compared with the total cost of numerical method. The convergence characteristics for both the cases have been observed and shown in Figures 3 (a) and 3 (b). In second case, where the transmission loss is considered, the Hopfield neural network method also shows good results. The proposed ANN technique for solving optimal generation dispatch problem with multiple fuel options was implemented in MATLAB language which was run on a 2.4 GHz Pentium IV machine. The average computation time for each load demand in case of ANN method was found to be about 40 s while the average computation time of the proposed numerical technique is about two min. This indicates that there is not much difference in computation time. But, when

Table 4 Comparison of optimal generation dispatch results obtained from Hopfield neural network and the numerical method considering loss

Load, MW	Numerical method[20]			Hopfield neural network method			Power mismatch, MW
902	Gen 1, MW	:	213.7862	Gen 1, MW	:	213.7144	0.2091
	Gen 2, MW	:	208.1258	Gen 2, MW	:	208.0945	
	Gen 3, MW	:	266.3219	Gen 3, MW	:	266.2377	
	Gen 4, MW	:	235.8940	Gen 4, MW	:	235.8722	
	Total loss, MW	:	22.1278	Total loss, MW	:	22.1188	
	Total power, MW ($P_1+P_2+P_3+P_4$)	:	924.1279	Total power, MW ($P_1+P_2+P_3+P_4$)	:	923.9188	
	Total cost, Rs/h	:	182.2831	Total cost, Rs/h	:	182.1839	
912	Gen 1, MW	:	217.3946	Gen 1, MW	:	217.2501	0.4177
	Gen 2, MW	:	209.6812	Gen 2, MW	:	209.6194	
	Gen 3, MW	:	270.5507	Gen 3, MW	:	270.3817	
	Gen 4, MW	:	236.9535	Gen 4, MW	:	236.9111	
	Total loss, MW	:	22.5806	Total loss, MW	:	22.5623	
	Total power, MW ($P_1+P_2+P_3+P_4$)	:	934.5800	Total power, MW ($P_1+P_2+P_3+P_4$)	:	934.1623	
	Total cost, Rs/h	:	187.3134	Total cost, Rs/h	:	187.1096	
922	Gen 1, MW	:	221.0075	Gen 1, MW	:	220.9353	0.2092
	Gen 2, MW	:	211.2398	Gen 2, MW	:	211.2084	
	Gen 3, MW	:	274.7773	Gen 3, MW	:	274.6929	
	Gen 4, MW	:	238.0147	Gen 4, MW	:	237.9934	
	Total loss, MW	:	23.0393	Total loss, MW	:	23.0301	
	Total power, MW ($P_1+P_2+P_3+P_4$)	:	945.0393	Total power, MW ($P_1+P_2+P_3+P_4$)	:	944.8301	
	Total cost, Rs/h	:	192.4810	Total cost, Rs/h	:	192.0626	
932	Gen 1, MW	:	224.6252	Gen 1, MW	:	224.5166	0.9141
	Gen 2, MW	:	212.7993	Gen 2, MW	:	212.7526	
	Gen 3, MW	:	279.0025	Gen 3, MW	:	278.8757	
	Gen 4, MW	:	239.0770	Gen 4, MW	:	239.0451	
	Total loss, MW	:	23.5040	Total loss, MW	:	23.4899	
	Total power, MW ($P_1+P_2+P_3+P_4$)	:	956.1040	Total power, MW ($P_1+P_2+P_3+P_4$)	:	955.1899	
	Total cost, Rs/h	:	197.7862	Total cost, Rs/h	:	197.6250	

implemented in hardware, the proposed neural network technique can achieve much faster real time response than the numerical technique. Therefore, the proposed ANN based technique promises to have a good merit in its applications.

CONCLUSION

This paper presents an ANN method consisting of radial basis function ANN, Hopfield ANN methods along with a heuristic rule based search algorithm for optimal generation dispatch solutions with multiple fuel options. Initially, a numerical technique as proposed in this paper is applied to find out the economic fuel option for each unit corresponding to a particular load demand which is used for generation of training patterns for the radial basis function ANN. Once this ANN is trained, then for a given load demand, a preliminary economic fuel option for each generating unit is obtained. Thereafter, a simple heuristic rule based algorithm is developed to reach a correct economic fuel option, *ie*, an integer value for each output. After obtaining the economic fuel option for each generating unit corresponding to a given load demand, the optimal generation dispatch result is obtained by a Hopfield neural network which satisfies the operational constraints. The simulation results show that the solution method is practical and valid for real time operation. An advantage of the proposed method is its capability to optimize over a greater variety of operating conditions. The proposed ANN method has applications to fossil fuelled generation units capable of burning coal, gas, and/or oil as well as other problems which result in multiple intersecting cost curves for a particular generating unit. This neural network method has the special advantage of solving the generation dispatch problems without calculating incremental fuel costs and incremental losses required by conventional numerical methods.

REFERENCES

1. B H Chowdhury and S Rahman. 'A Review of Recent Advances in Economic Dispatch.' *IEEE Transactions on Power Systems*, vol 5, no 4, 1990, p 1248.

2. D C Walters and G B Sheble. 'Genetic Algorithm Solution of Economic Dispatch with Valve Point Loading.' *IEEE Transactions on Power Systems*, vol 8, no 3, 1993, p 1325.

3. M E El-Hawary and G S Christensen. 'Optimal Economic Operation of Electric Power Systems.' *Academic Press*, 1979.

4. J Freeman and D Skapura. 'Neural Networks Algorithms – Applications and Programming Techniques.' *Addison-Wesley Publishing Company, Inc*, 1991.

5. P K Kalra and A Srivastava. 'Possible Applications of Neural Nets to Power System Operation and Control.' *Electric Power Systems Research*, vol 25, 1992, p 83.

6. M El-Sharkawi, R Marks and S Weerasooriya. 'Neural Networks and their Application to Power Engineering.' *Academic Press*, 1991.

7. V S S Vankayala and N D Rao. 'Artificial Neural Networks and their Applications to Power Systems – A Bibliographical Survey.' *Electric Power Systems Research*, vol 28, 1993, p 67.

8. B Novak. 'Superfast Autoconfiguring Artificial Neural Networks and their Application to Power Systems.' *Electric Power Systems Research*, vol 35, 1995, p 11.

9. J Park and I W Sandberg. 'Universal Approximation using Radial basis Function Networks.' *Neural Computation*, vol 3, no 2, 1991, p 246.

10. J J Hopfield. 'Neural Networks and Physical Systems with Emergent Collective Computational Abilities.' *Proceedings of the National Academy of Science*, USA, vol 79, April 1982, p 2554.

11. J J Hopfield. 'Neurons with Graded Response have Collective Computational Properties like those of Two-state Neurons.' *Proceedings of the National Academy of Science*, USA, vol 81, May 1984, p 3088.

12. J J Hopfield and D W Tank. 'Neural Computation of Decisions in Optimization Problems.' *Biological Cybernetics*, vol 52, 1985, p 141.

13. D W Tank and J J Hopfield. 'Simple Neural Optimization Networks : an A/D Converter, Signal Decision Circuit and a Linear Programming Circuit.' *IEEE Transactions on Circuits and Systems*, vol CAS -33, no 5, 1986, p 533.

14. M P Kennedy and L O Chua. 'Unifying the Tank and Hopfield Linear Programming Circuit and the Canonical Non-linear Programming Circuit of Chua and Lin.' *IEEE Transactions on Circuits and Systems*, vol CAS-34, no 2, 1987, p 210.

15. H Sasaki, M Watanabe and R Yokoyama. 'A Solution Method of Unit Commitment by Artificial Neural Networks.' *IEEE Transactions on Power Systems*, vol 7, no 3, 1992, p 974.

16. T D King, M E El-Hawary and F El-Hawary. 'Optimal Environmental Dispatching of Electric Power Systems via an Improved Hopfield Neural Network Model.' *IEEE Transactions on Power Systems*, vol 10, no 3, 1995, p 1559.

17. Y Ueki and Y Fukuyama. 'An Application of Artificial Neural Network to Dynamic Economic Load Dispatching.' *Proceedings of the First International Forum on the Application of Neural Networks to Power Systems*, Scattle, July 1991, p 261.

18. J H Park, Y S Kim, I K Eom and K Y Lee. 'Economic Load Dispatch for Piecewise Quadratic Cost Function using Hopfield Neural Network.' *IEEE Transactions on Power Systems*, vol 8, no 3, 1993, p 1030.

19. J J Hopfield and D W Tank. 'Computing with Neural Circuits : A Model.' *Science*, vol 233, 1986, p 625.

20. P K Hota and S K Dash. 'Economic Load Dispatching of Generating Units with Multiple Fuel Options.' *Journal of The Institution of Engineers (India)*, vol 88, EL/1, June, 2007, p 22.